Recovering Surface Normal and Arbitrary Images: A Dual Regression Network for Photometric Stereo

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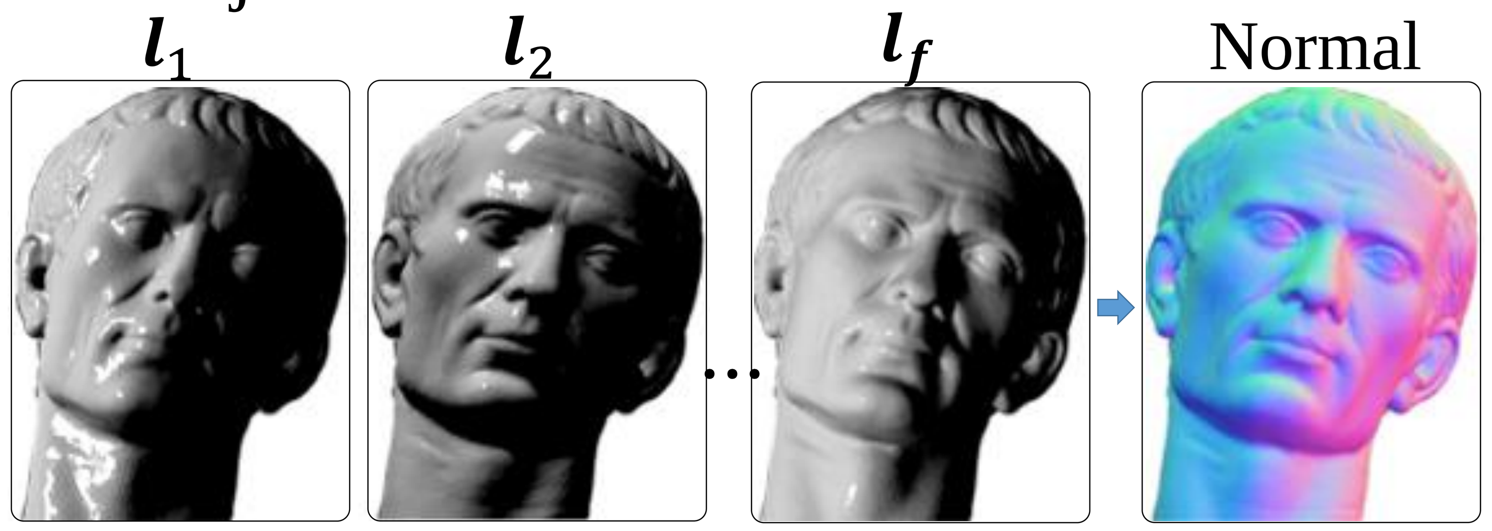
Background & Motivation

Photometric stereo recovers the dense surface normal of the object under different illumination directions.

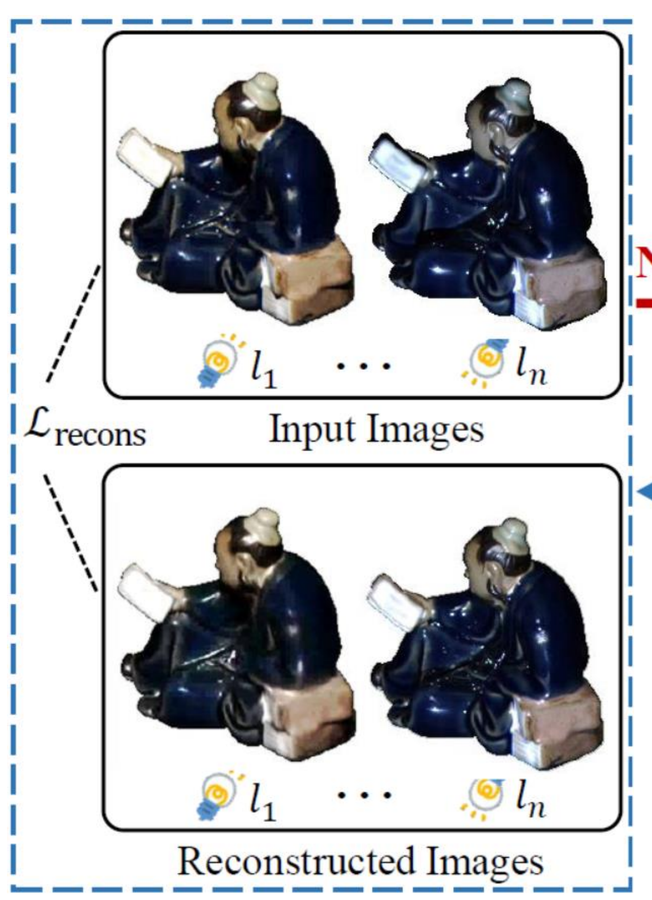


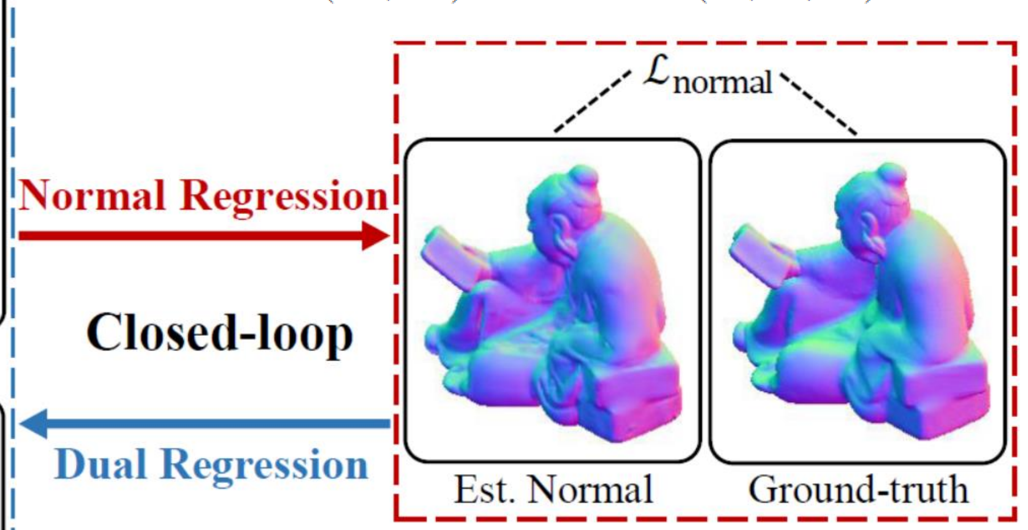
The previous learning-based methods focus on the surface normal constraint without other supervision.

Method

DR-PSN, forming a closed-loop structure to provide additional constrain. The dual regression task learns the imaging model, which is the inverse task of and improves the surface normal estimation.

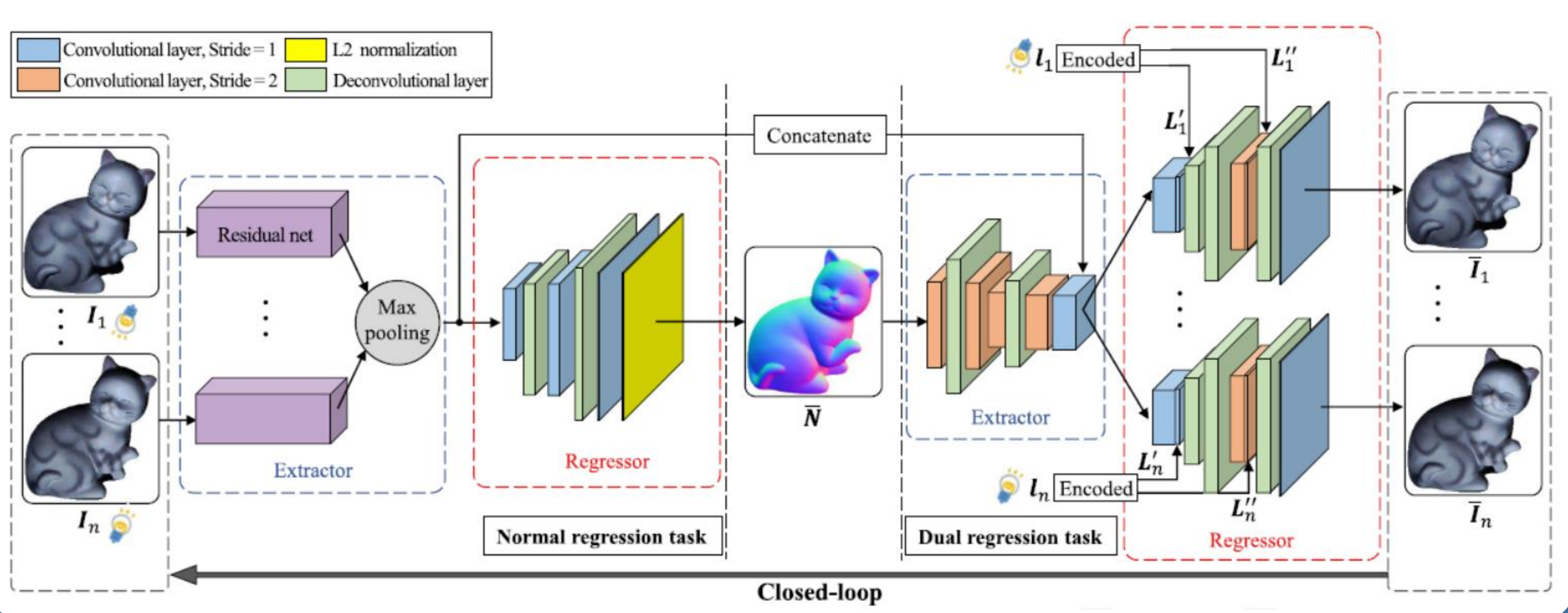
$$\mathcal{L} = \mathcal{L}_{\text{normal}}(\bar{N}, N) + \lambda_t \mathcal{L}_{\text{recons}}(\bar{I}_i, I_i, \forall i)$$





$$\mathcal{L}_{\text{normal}}(\bar{N}, N) = \frac{1}{HW}\sum_{p}^{HW}(1 - \bar{N}_p \odot N_p)$$

$$\mathcal{L}_{\text{recons}}(\bar{I}_i, I_i, \forall i) = \frac{1}{n}\sum_{i=1}^{n}\|\bar{I}_i - I_i\|_2^2$$



Experimental Results

Ablations with varying λ_t

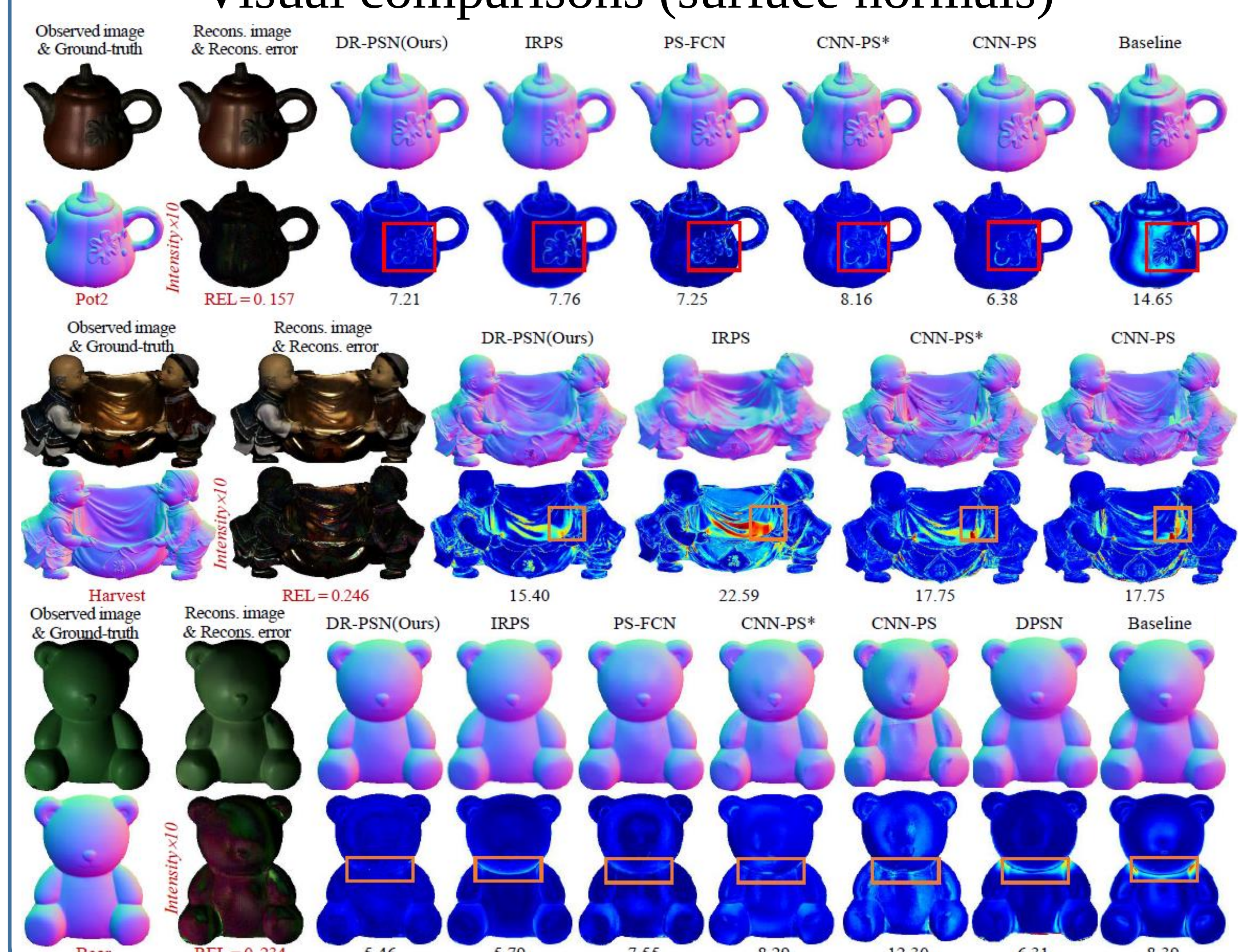
Variants	Surface normal		Reconstructed images	
	MAE (°) ↓	$< err_{15°}$ ↑	SSIM ↑	REL ↓
Dual, proposed linear λ_t ($\Delta = 0.02$, PT= 0.8)	**11.47**	84.99%	0.947	0.171
Single $\lambda = 0$	12.53	81.55%	-	-
Dual, fixed $\lambda = 0.1$	11.64	84.61%	0.895	0.235
Dual, fixed $\lambda = 0.5$	11.88	82.94%	0.939	0.182
Dual, fixed $\lambda = 1$	12.50	81.79%	**0.963**	**0.166**
Dual, linear λ_t ($\Delta = 0.02$, PT= 0.6)	11.57	**85.01%**	0.926	0.197
Dual, linear λ_t ($\Delta = 0.02$, PT= 1)	11.80	83.33%	0.951	0.169
Dual, linear λ_t ($\Delta = 0.01$, PT= 0.8∗)	11.58	84.52%	0.914	0.209
Dual, linear λ_t ($\Delta = 0.04$, PT= 0.8)	11.55	84.39%	0.929	0.175
Dual, quadratic λ_t ($\Delta = 0.001$, PT= 0.8)	11.49	84.95%	0.916	0.197
Dual, quadratic λ_t ($\Delta = 0.0005$, PT= 0.8)	11.58	84.78%	0.934	0.188

DiLiGenT benchmark with inputs 96 & 10

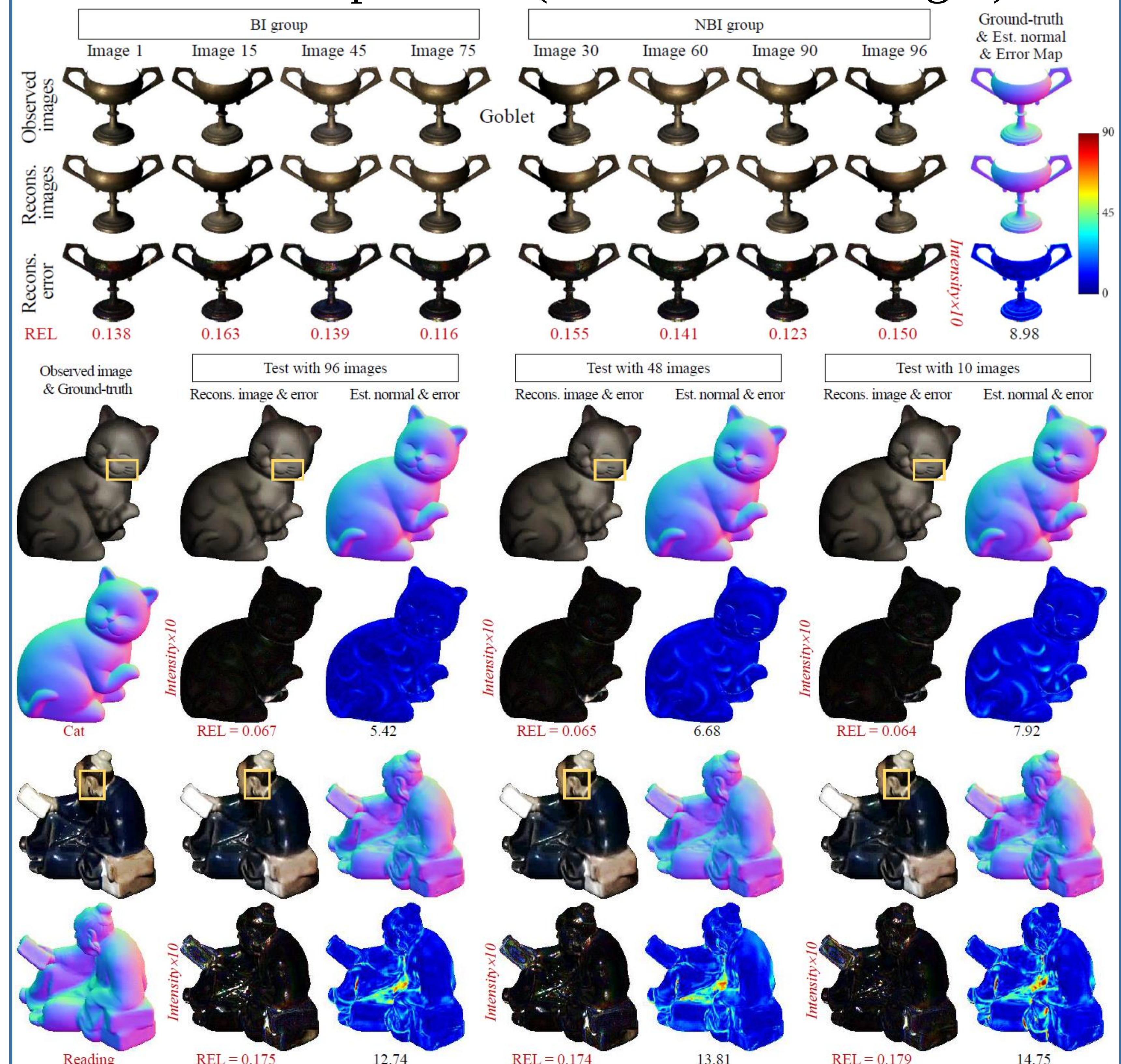
Method	Ball	Bear	Buddha	Cat	Cow	Goblet	Harvest	Pot1	Pot2	Reading	Avg.
Baseline (Least squares) [1]	4.10	8.39	14.92	8.41	25.60	18.50	30.62	8.89	14.65	19.80	15.39
Matrix rank = 3 [22]	2.54	7.32	11.11	7.21	25.70	16.25	29.26	7.74	14.09	16.17	13.74
Bivariate BRDF [26]	3.34	7.11	10.47	6.74	13.05	9.71	25.95	6.64	8.77	14.19	10.60
Bi-polynomial [28]	1.74	6.12	10.60	6.12	13.93	10.09	25.44	6.51	8.78	13.63	10.30
SDPS-Net [11]	2.77	6.89	8.97	8.06	8.48	11.91	17.43	8.14	7.50	14.90	9.51
DPSN [10]	2.02	6.31	12.68	6.54	8.01	11.28	16.86	7.05	7.86	15.51	9.41
IRPS [40]	**1.47**	5.79	10.36	5.44	**6.32**	11.47	22.59	6.09	7.76	**11.03**	8.83
CNN-PS* [12]	2.23	8.29	8.53	5.75	9.74	8.66	17.75	5.91	8.16	11.61	8.66
PS-FCN [13]	2.82	7.55	7.91	6.16	7.33	8.60	15.85	7.13	7.25	13.33	8.39
CNN-PS [12]	2.12	12.30	8.07	**4.38**	7.92	**7.42**	**13.83**	**5.37**	**6.38**	12.12	7.99
DR-PSN (Ours)	2.27	**5.46**	**7.84**	5.42	7.01	8.49	15.40	7.08	7.21	12.74	**7.90**

Method	Ball	Bear	Buddha	Cat	Cow	Goblet	Harvest	Pot1	Pot2	Reading	Avg.
Bivariate BRDF [26]	12.94	16.40	20.63	15.53	18.08	18.73	32.50	**6.28**	14.31	24.99	19.04
Baseline (Least squares) [1]	5.09	11.59	16.25	9.66	27.90	19.97	33.41	11.32	18.03	19.86	17.31
Bi-polynomial [28]	5.24	9.39	15.79	9.34	26.08	19.71	30.85	9.76	15.57	20.08	16.18
Matrix rank =3 [22]	**3.33**	7.62	13.36	8.13	25.01	18.01	29.37	8.73	14.60	16.63	14.48
CNN-PS [12]	9.11	14.08	14.58	11.71	14.04	15.48	19.56	13.23	14.65	16.99	14.34
CNN-PS* [12]	6.39	14.51	15.08	10.96	15.26	14.40	19.73	11.35	13.58	16.67	13.79
PS-FCN [13]	4.02	**7.18**	9.79	8.80	10.51	11.58	18.70	10.14	9.85	15.03	10.51
SPLINE-Net [38]	4.96	5.99	10.07	7.52	**8.80**	10.43	19.05	8.77	11.79	16.13	10.35
LMPS [37]	3.97	8.73	11.36	**6.69**	10.19	10.46	17.33	7.30	9.74	**14.37**	10.02
DR-PSN (Ours)	3.83	7.52	**9.55**	7.92	9.83	**10.38**	**17.12**	9.36	**9.16**	14.75	**9.94**

Visual comparisons (surface normals)



Visual comparisons (reconstruction images)



Evaluation on the Light Stage Data Gallery

Extended Work

Our extended work (submitting) can render both arbitrary light and reflectance of the image, which will expand the limited dataset of photometric stereo.

Feel free to contact me via **juyakun@stu.ouc.edu.cn**, whether meets any questions about any photometric stereo papers of mine, or for cooperation.

[**Citation**] Ju, Yakun, Junyu Dong, and Sheng Chen. "Recovering Surface Normal and Arbitrary Images: A Dual Regression Network for Photometric Stereo." *IEEE Transactions on Image Processing* 30 (2021): 3676-3690.